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Feedback regulation of an industrial aerobic wastewater plant

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Abstract

The main task of this work is related with the design of a class of SISO robust control law for the regulation of substrate concentration measured as chemical demand of oxygen (CDO) of an industrial activated sludge wastewater plant. The control design is related with an uncertainty estimator (reduced order observer)-based active control. Departing from the dynamic error between the desired and the current substrate concentration trajectories a control law is designed and the plant is regulated to the corresponding set point of the COD concentration. To be realizable the controller needs model information related with the kinetic term of COD (substrate) consumption which is provided with a reduced order observer, this coupled structure (observer-based controller) is robust against model uncertainties. The performance of the proposed control law is illustrated with numerical simulations employing a mathematical model of an industrial activated sludge wastewater plant tuned with industrial data.
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1. Introduction

Operating and controlling a wastewater treatment plant is not a simple task, raw wastewater varies continuously in quantity and composition and the heart of the process, the biomass, also changes under the influence of internal and external factors. To get an adequate plant performance, the operational variables can be adapted in any given situation to meet actual requirements; these changes are based on taking measurements of relevant process parameters using grab or composite samples for further monitoring and control tasks, however the lack of liable measurements is a serious drawback in the operation of this kind of process.

Several kinds of control strategies have been proposed for biological processes, depending of the operation mode, for example, for batch and feed-batch processes, where optimal concentration profiles must be exploited; techniques as optimal and adaptive controllers have been proposed with success, these methodologies employ state and uncertainty observers to infer unmeasured variables, which are coupled with some control laws to provide optimal substrate concentrations in the bioreactor which tend to minimize the reaction time, improving the performance of the operation [1–5]. On the other hand, the continuous mode of operation, where an optimum steady-state must be reached, several approaches such as H_∞, predictive and neuro-controller have been considered for regulation purposes [6–10]. They have shown an adequate performance for a class of bioreacting systems, however, some of them are coupled with optimizing routines or are model-based; their main drawbacks are over-parameterization and lack of robustness under model uncertainties. Other family of control designs is related with the nonlinear approach [11], where the generic, linearizing, and active controllers, which belong to the named generalized linearizing control, have been employed adequately, too. These approaches cancel the nonlinearities of the systems and try to impose a desired behavior for regulation and tracking purposes, however, considering that they are model based, robust generalized linearizing controller based on state and/or uncertainty, observations have been presented in the open literature [12–16].

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Recently, the standard active control (AC) has been employed to control systems with high nonlinear behavior, in this methodology the controller design is based on the dynamics of the control error, i.e. the difference between the current and the desired trajectory of the system. This methodology has been successfully employed for synchronization of chaotic oscillators for security data transmission [17–19], but design of explicit controllers with application to regulation of reacting process, as the authors known, have not been studied enough. The realization of the corresponding active control law is model based, such that the controller tries to cancel the nonlinearities and impose a stable behavior, such that under model uncertainties the standard AC is not applicable. To avoid the problem mentioned above, in this work is proposed an observer-based active control, where a reduced order observer is designed to provide the corresponding missing information (uncertain terms, related with modeling errors) to the controller and assuring a stable closed-loop behavior.

2. The industrial aerobic wastewater plant

Wastewater engineering represents, at present time, a subject area of worldwide interest, for reasons of public health, economic and social issues to which it is closely associated. In particular, the wastewater generated by industrial processes is a very important topic for engineering research; from them the petrochemical industry under study produces a wastewater which is generated in the different chemical processes. The wastewater flow produced is about 7000 m^3/d and contains volatile organic carbon's substances classified as toxics like 1,2-dichloroethane, chloroform, benzene, among other volatile compounds (VOCs). To comply the Mexican environment legislation [20] is around of 150 mg/L (2007 perspective) in order to discharge the wastewater treated into the river. One of the main effects on the plant operation is the actual temperature condition within the bioreactor which is 32 °C in October–November reaching up to 41 °C in August–September. Due to this effect, the microorganism's activity is affected, and this must be considered in the dynamic modeling of the system. Some models have been developed to describe the effect of temperature on bacterial growth [21–23]. The authors showed that at high temperatures the maximum specific growth rate ($\mu_{\max}$) is reduced.

For control purposes a mathematical model of an activated sludge process is employed, this model presented in [24,25] consider a simple carbon removal model with an dynamic energy balance to introduce the temperature effects on the maximum specific growth rate, mass transfer coefficient for oxygen (kla) and death coefficient (k_d), which were incorporated in the mass balance equations of the process.

The temperature effect on the maximum specific growth rate was evaluated with Eq. (7), the mass transfer coefficient for the oxygen (kla) with Eq. (9) which is an empirical function of the air flow [26], the death coefficient (k_d) with Eq. (8) the evaporation flux of VOCs ($K_{ev}S$) is also considered in the COD balance, together with the inactivate biomass $(1-f_n)X$ which contributes to the growth of the substrate concentration in the bioreactor—all were incorporated in the mass balance equations of the process.

The process is described by the following balance equations, as a first modeling approach of the temperature effect on different parameters is considered introducing an energy balance considering that the metabolic heat generation can be deleted in comparison with the other energy flows. The bioreactor behavior was assumed as a completely mixed flow reactor.

In the reactor:

- Substrate (S) concentration mass balance:

$$\frac{dS}{dt} = \frac{Q_f}{V}S_f - \frac{Q_O}{V}S - \frac{\mu_{\max}}{Y}\left(\frac{S}{K_s+S}\right)\left(\frac{C_{O_2}}{K_{OH}+C_{O_2}}\right)X + (1-f_n)X - K_{ev}S \quad (1)$$

- Biomass (X) concentration mass balance:

$$\frac{dX}{dt} = \frac{Q_r}{V}X_r - \frac{Q_O}{V}X + \mu_{\max}\left(\frac{S}{K_s+S}\right)\left(\frac{C_{O_2}}{K_{OH}+C_{O_2}}\right)X - k_d X \quad (2)$$

- Oxygen (C_{O_2}) concentration mass balance:

$$\frac{dC_{O_2}}{dt} = \frac{Q_f}{V}C_{O_2f} - \frac{Q_O}{V}C_{O_2} - \frac{\mu_{\max}}{Y_{O_2}}\left(\frac{S}{K_s+S}\right) \times \left(\frac{C_{O_2}}{K_{OH}+C_{O_2}}\right)X + \text{kla}(C_{O_{2sat}} - C_{O_2}) \quad (3)$$

- Energy balance (T):

$$\frac{dT}{dt} = \frac{Q_O}{V}(T_{in}-T) + \frac{Q_{air}\rho_{air}C_{p_{air}}}{V_\rho C_p}T_{air} + \frac{h_c A}{V_\rho C_p}(T - T_\infty) \quad (4)$$

It was assumed that there was no biomass in the overflow of the settler [14].

In the settler:

$$\frac{dX_r}{dt} = \frac{Q_U}{V_S}X_r - \frac{Q_O}{V_S}X \quad (5)$$

and

$$Q_O = Q_f + Q_r, \qquad Q_U = Q_W + Q_r$$

where A is the transport area (m^2), t the time (d), h_c the heat transfer coefficient, Q_f the influent flow rate (m^3/d), Q_r the recycle flow rate (m^3/d), Q_W the waste flow rate (m^3/d), Q_{air} the air flow rate (m^3/d), S_f the COD concentration in the influent (mg/L), S the COD concentration in the reactor (mg/L), X the biomass concentration in the reactor (mg/L), X_r the biomass concentration in the settler (mg/L), C_{O_2f} the dissolved oxygen concentration in the influent (mg/L), C_{O_2} the dissolved oxygen concentration in the reactor (mg/L) and $C_{O_{2sat}}$ is the dissolved oxygen saturation concentration (mg/L):

$$\mu = \text{specific growth rate}\,(d^{-1}) = \frac{\mu_{\max}S}{K_s+S} \quad (6)$$

$$\mu_{\max} = \text{maximum specific growth rate}\,(\mathrm{d}^{-1}) = b^2(T-285)^2\{1-\exp[c(T-330.5)]\}^2 \quad (7)$$

where $b = 0.05$ ($\mathrm{K}^{-1}\,\mathrm{h}^{-0.5}$), $c = 0.005$ (K^{-1}), $K_s = 30$ mg/L (substrate saturation coefficient) and $K_{OH} = 0.2$ mg/L (substrate saturation coefficient):

$$k_d = \text{death coefficient}\,(\mathrm{d}^{-1}) = k_{d\,20}1.05^{(T-20)} \quad (8)$$

where $k_{d\,20} = 0.03\,\mathrm{d}^{-1}$ = death coefficient at 20 °C, $Y_{x/s} = 0.67$ = yield coefficient (mg biomass produced/mg COD consumed) and $Y_{O_2} = 2.03$ = yield oxygen coefficient (mg biomass produced/mg O_2 consumed):

$$\mathrm{kla} = \text{mass transfer coefficient}\,(\mathrm{d}^{-1}) = \mathrm{kla}_{20}1.02^{(T-20)} \quad (9)$$

where $\mathrm{kla}_{20} = 166(1-\exp(-Q_{\mathrm{air}}/23{,}040))$ is the mass transfer coefficient at 20 °C (d^{-1}), T = wastewater temperature in the reactor (°C), $V = 15{,}000\,\mathrm{m}^3$ (reactor volume), $V_S = 750\,\mathrm{m}^3$ (settler volume), ρ = density (g/cm^3) and C_p = heat capacity (kcal/g °C).

3. Robust active control

3.1. Problem statement

The objective of a wastewater plant is to transform pollutants and even toxic compounds into more environment friendly substances, in most of the cases the treated water must comply with some maximum of pollutant substances in accordance with legislation rules, these restrictions generally fix the corresponding set points to be reached. In view of the particular characteristic of this kind of process, the operation is a difficult issue. For the control of aerobic wastewater plant, several strategies have been proposed, considering several input–output selections and SISO and MIMO control structures for fed-batch and continuous bioreactors. In this work a SISO control structure is considered, for the sake of simplicity, to show how the active control (AC) can be implemented, following the pair of control and controlled variables proposed in [27,28]; the COD (substrate) concentration is considered as the controlled measured output (y). The COD is the amount of oxygen required to oxidize, by chemical means, organic carbon compounds completely to CO_2 and H_2O, and it is measured routinely in industrial operation [6]; the corresponding control input (u) is related with the input flow, which affect the input substrate concentration rate. With the above, let us analyze the following subsystem related with the substrate mass balance equation:

$$\frac{\mathrm{d}S}{\mathrm{d}t} = \frac{Q_f}{V}S_f - \frac{Q_O}{V}S - \vartheta \quad (10)$$

with

$$\vartheta = \frac{\mu_{\max}}{Y}\left(\frac{S}{K_s+S}\right)\left(\frac{C_{O_2}}{K_{OH}+C_{O_2}}\right)X + (1-f_n)X + K_{ev}S$$

as the total COD consumption rate.

Note that the term $\vartheta(\cdot)$ contains the COD kinetic rate, the non-activate biomass and the volatile substrate. Now, it is proposed a desired COD closed-loop trajectory as follows:

$$\frac{\mathrm{d}y_d}{\mathrm{d}t} = -\alpha(y_d - y_{sp}) \quad (11)$$

This desired output trajectory allows reaching the corresponding set point y_{sp} asymptotically with a convergence rate given by the parameter α.

Now, defining the control error as

$$e = S - S_d = y - y_d \quad (12)$$

then

$$\dot{e} = \alpha(y_d - y_{sp}) - \vartheta(\circ) - \frac{Q_O}{V}y + u(t) \quad (13)$$

from the above, the following controller is proposed, applying the AC methodology:

$$u(t) = \frac{Q_f}{V}S_f = \alpha y_{sp} + \vartheta(\circ) + \zeta(t) \quad (14)$$

such that this controller provides the following closed-loop structure of the control error dynamic:

$$\dot{e} = \alpha y_d - \frac{Q_O}{V}y + \zeta(t) \quad (15)$$

or in alternative form:

$$\dot{e} = -\frac{Q_O}{V}e + \left(\alpha - \frac{Q_O}{V}\right)y_d + \zeta(t) \quad (16)$$

the exogenous function ζ is chosen such that it can provide a stable behavior to the control error trajectory, in accordance with the following structure:

$$\zeta(t) = -\left(\alpha - \frac{Q_O}{V}\right)y_d \quad (17)$$

Note that the control input depends on the nonlinear term $\vartheta(\cdot)$, consequently the controller is realizable only if the nonlinear term is known, which is an important drawback for the standard AC implementation when modeling errors are present.

3.2. Robust active control law

One of the major bottlenecks in the application of computer monitoring and control for biological process is the lack of reliable, sterilizable and robust sensors for the on-line measurements of process key variables, such as biomass, precursors, product concentrations and consumption rates. Several attempts to quantify the above variables have been employed, some of them are optical techniques, other include electrochemical detection and detection by viscosity, filtration and fluorescence methods [29], but these approaches frequently do not properly address the most important industrial problems and necessities.

To tackle the problems mentioned above, several estimation techniques for the bioprocess have been developed. These techniques are often named soft-sensors. Some of them are based on balancing technique. This approach is adequate for steady-state operation, however it becomes unstable when dynamic and corrupted measures are presented [30]; on the other hand filtering (observing) theory where extended Kalman filters, nonlinear Luenberger observers, sliding-mode, high gain and so on have been successfully employed [31–34]. Considering our particular case, the state variable to be regulated is directly the measures output of the system, i.e. the COD concentration such that, a reduced order observer to infer the uncertain term $\vartheta(\circ)$ is proposed as follows:

$$\frac{d\hat{\vartheta}}{dt} = \tau(\vartheta_{obs} - \hat{\vartheta}) \tag{18}$$

where τ is the observer gain, $\hat{\vartheta}$ the estimate of the uncertain term and the observed uncertainty ϑ_{obs} is obtained by solving the mass balance equation, in accordance with the next equation:

$$\vartheta_{obs} = -\frac{dy}{dt} + \frac{Q_f}{V}S_f - \frac{Q_O}{V}y \tag{19}$$

As it can be seen, the structure of the proposed observer includes the derivative of the COD concentration, which must be calculated in order to obtain estimates of the reaction rate. However, the synthesis of derivators is a difficult task; moreover, if the concentration measurements are noisy, the synthesis would be impossible. In order to avoid this situation the following change of variable is proposed:

$$\Theta = \hat{\vartheta} + \tau y \tag{20}$$

Producing an uncertainty observer with the following structure:

$$\frac{d\Theta}{dt} = \tau\left(\frac{Q_f}{V}S_f - \frac{Q_O}{V}y - \hat{\vartheta}\right) \tag{21}$$

Note that with Eqs. (20) and (21) the uncertain term can be expressed finally as

$$\hat{\vartheta} = \Theta - \tau y \tag{22}$$

As can be seen, this estimation methodology given by Eqs. (21) and (22) depends only on measured variables, avoiding the output time derivative. Now, for the realization of the robust (non-ideal) AC, the estimate of the uncertain term determined above is coupled with the ideal AC to produce:

$$u(t) = \alpha y_{sp} + \hat{\vartheta}(\circ) + \zeta(t) \tag{23}$$

Note that the above no ideal controller can recover its ideal properties if the estimation error $e_1 = \vartheta_{obs} - \hat{\vartheta}$ tends to zero. To prove this, let us consider the convergence analysis of the proposed observer, departing from the unknown dynamic of the uncertain term:

$$\frac{d\vartheta_{obs}}{dt} = \Phi(\circ) \tag{24}$$

Eq. (18) is an asymptotic proportional reduced observer for the system given by Eq. (24), where $\tau > 0$, determines the desired convergence rate of the observer, if the following assumptions are satisfied.

There exist τ and $N \in \Re^+$ such that:

A1. The dynamic of the uncertain term is bounded, i.e. $||\Phi(\circ)|| \le N$

A2. $\limsup_{t\to\infty} \left\| \exp\left(-\int_0^t \tau\, d\sigma\right)\right\| = 0$

Considering the above Eq. (24), the dynamic of the estimation error is defined as

$$\dot{e}_1 + \tau e_1 = \Phi(\circ) \tag{25}$$

Solving it renders:

$$e_1 = \exp\left(-\int_0^t \tau\, d\sigma\right)\left[e_{10} + \int_0^t \exp\left(\int_0^s \tau\, d\sigma\right)\Phi(\circ)\, ds\right] \tag{26}$$

where e_{10} is the initial condition of the estimation error. Taking norms of Eq. (26) the following inequalities arises:

$$0 \le \limsup_{t\to\infty} ||e_1|| \le ||e_{10}|| \limsup_{t\to\infty}\left[\left\|\exp\left(-\int_0^t \tau\, d\sigma\right)\right\|\right] + \limsup_{t\to\infty} \frac{\left[\int_0^t \left\|\exp\left(\int_0^s \tau\, d\sigma\right)\Phi(\circ)\, ds\right\|\right]}{\left\|\exp\left(\int_0^t \tau\, d\sigma\right)\right\|} \tag{27}$$

From assumptions (A1) and (A2):

$$0 \le \limsup_{t\to\infty} ||e_1(t)|| \le \limsup_{t\to\infty} \frac{\left[N\int_0^t \left\|\exp\left(\int_0^s \tau\, d\sigma\right)\, ds\right\|\right]}{\left\|\exp\left(\int_0^t \tau\, d\sigma\right)\right\|}$$

The above equation means that the ∞/∞ case of uniform L'Hôpital's Rule can be applied as follows:

$$0 \le \limsup_{t\to\infty} ||e_1(t)|| \le \limsup_{t\to\infty} \frac{N\left\|\exp\left(\int_0^t \tau\, d\sigma\right)\right\|}{\left\|\exp\left(\int_0^t \tau\, d\sigma\right)\right\| ||\tau||} = \limsup_{t\to\infty} \frac{N}{||\tau||}$$

Therefore

$$|e_1| \le \frac{N}{||\tau||} \tag{28}$$

Beside, the above inequality implies that the estimation error can be as small as is desired, if the observer gain τ is chosen large enough.

Considering the inequality (28), it can be concluded that the estimation error e_1 converges to the closed ball $B_r(0)$ with radius $r = N/||\tau||$ producing practical convergence. Note that if the system output is corrupted by additive noise, i.e. $y = S = \xi$, and the noise is considered bounded such that $||\xi|| \le \Lambda$, a similar methodology used to analyze the estimation error e_1 can be applied in order to prove that the steady-state estimation error becomes $(N + \Lambda)/\tau$ which shows robustness against noisy measurements.

3.3. Remarks

In almost all cases, the substrate measurements are discrete due to the characteristics of the sensors for this class of processes introducing a delay for the system; therefore a discrete synthesis of the uncertainty estimator and the corresponding control law must be done. The main tasks of the digital observers and controllers are very close to the continuous ones, i.e. no steady-state offsets and closed-loop stability. Generally speaking, the discrete designs can be done for one of the following two ways [35]: the first is to carry out the design directly in discrete time and obtain the discrete design. The main advantages of this approach are that all the effects of discretization and sampling are directly incorporated into the design procedure, and the observer and control law resulting are only limited by realizability conditions. However, one of the principal disadvantages is the continuous nature of the process. This may not easily take into account the strictly discrete version, such that it is possible to generate closed-loop behaviors that meet good performance at sampling points while showing poor behavior between samples. This can be the case of continuous bioreactors with complex dynamics. The second one, which is the considered approach on this paper, is to carry out controller design in a more familiar continuous time domain. The main advantage of relying on controller design principles is already familiar, and allows the employment of all the theoretic developments on dynamic systems for stability and performance issues. In this case, considering that the residence time of the wastewater plant is about 48 h, and the sampling period is of 1 h, the considerations mentioned above can be tackled in order to conserve the continuous approach results.

4. Results and discussion

The mathematical model was validated with the COD data obtained from the wastewater treatment plant which was in operation during a year, from October 2002 to September 2003 as presented previously in [36]. For simulation purposes a step disturbance in the recycle flow Q_r is considered from 525 to 551 mg/L, besides other step disturbance on the oxygen concentration at reactor input is also considered, from 3 to 2 mg/L. A commercial PI controller is simulated too for comparison purposes, the tuning of the PI control's gains was done via input–output response with a step disturbance in the control input, which yields the following parameters: the steady-state gain $K = 2.8$ mg d/L m^3; the characteristic time $\pi = 7$ d; the proportional control gain $K_p = 1.5\ d^{-1}$ and the integral time $\tau_I = 7$ d, these values were obtained applying IMC tuning rules [35]. For the robust AC controller the convergence rate $\alpha = 0.5\ d^{-1}$ and the observer gain $\tau = 1\ d^{-1}$ were considered. The initial conditions for COD, biomass, oxygen and biomass in the settler and temperature are 2200 mg/L, 1000 mg/L, 6500 mg/L, 2 mg/L and 303 K, respectively, and the initial condition for the uncertainty observer is 0.1 mg/d.

Fig. 1 is related with the closed-loop concentrations space portrait, note that the controller lead the COD concentration to the required set point (150 mg/L) with a biomass of 4200 mg/L and the dissolved oxygen is around 0.4 mg/L, which is the closed-loop steady-state. Fig. 2 shows the closed-loop time evolution of the COD concentration can be observed as an asymptotic stable behavior of the COD trajectory to the former set point which is reached in 12 d for the proposed controller this settling time can be reduced for the proposed AC controller with a more large value of the parameter α, in order to improve the convergence rate. The PI controller needs 52 d to reach the corresponding set point. Fig. 3 is related with

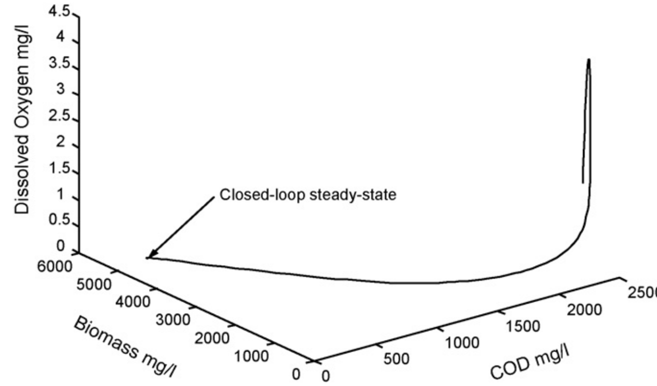

Fig. 1. Closed-loop steady-state phase portrait.

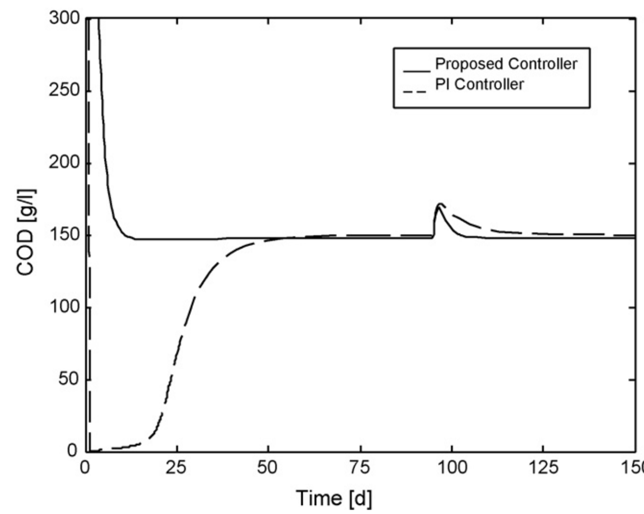

Fig. 2. Closed-loop performance of the COD.

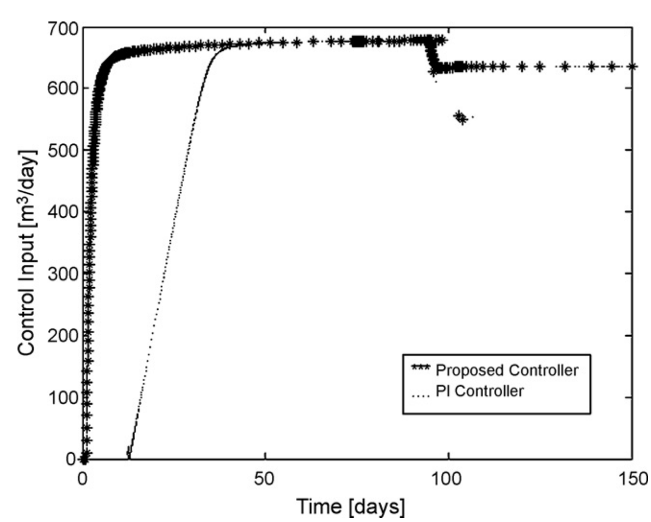

Fig. 3. Closed-loop performance of the system input (input flow).

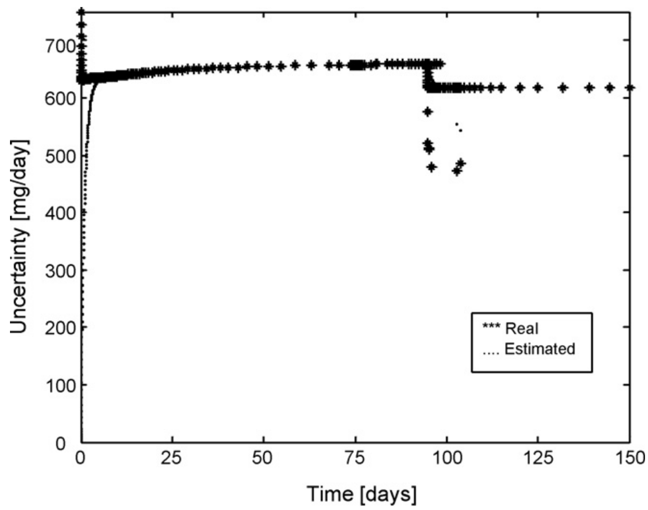

Fig. 4. Closed-loop uncertainty observer performance.

the closed-loop performance of the control output (COD concentration) when the disturbances arrive, the proposed AC controller has a faster response in comparison with the PI controller. Finally Fig. 4 shows the closed-loop performance of the reduced order observer, not a satisfactory performance of the proposed estimation methodology, this occurs because the proposed methodology is able to regulate the process into more wide operating region given its nonlinear properties and the low parameters dependence, which helps to avoid tuning issues.

5. Conclusions

A mathematical model of an activated sludge wastewater plant is developed and corroborated with industrial COD and operating data with good results. This model is employed as a *virtual* process where the total COD (substrate) consumption rate is supposed to be uncertain (unknown). To avoid the problem of the modeling errors a reduced order observer is proposed, the information generated by the observer is coupled with an active control law, such that a robust structure against modeling error is achieved. Numerical simulations illustrate the satisfactory performance of the observer-based AC law.

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